



Model Predictive Control Based on System Re-Identification for Methanol and Dimethyl Ether Synthesis Control

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Abstract

To improve the performance of the model predictive control (MPC) was carried out by improving the model used. In this study the improvement was carried out by a closed loop system re-identification. In addition, the MPC tuning was carried also to obtain a more optimum control performance. The MPC based on a system re-identification (MPC-SRI) was used to control the synthesis of methanol and dimethyl ether, and compared with the PI controller. The results provide better performance than PI controller by decreasing the errors for each unit as follows: 29,62% (IAE) and 1,51% (ISE) for TC (temperature control) Heater 1; 51,69% (IAE) and 79,04% (ISE) for TC Heater 2; 67,44% (IAE) and 82,24% (ISE) for TC Cooler 1; 49,07% (IAE) and 67,26% (ISE) for TC Cooler 2; 56,75% (IAE) and 53,03% (ISE) for PC (pressure control) Compressor; 4,46% (IAE) and 50,00% (ISE) for CC (composition control) DME.

Keywords: MPC, re-identification, methanol, DME

Introduction

Model predictive control (MPC) is an advanced process control method that has been in use in the process industries since the 1980s (Morari and Lee, 1999). While the inspiration began when Kalman filter (Kalman, 1960) was introduced, MPC was introduced in the late 1970's and early 1980's by Richalet *et al.* (1978) and Cutler (1983). Over the years, the technology has matured to be successfully applied to complex industrial processes (Xi *et al.*, 2013), and it is reasonable to say that MPC has become the *de facto* standard algorithm for advanced process control in process industries (Nikolaou, 1998). After about 20 years since its introduction, more than 600 industry applications were reported (Qin and Badgwell, 2003), and the current number is expected to be much larger. The key reason for the popularity of MPC in both the industry and the academic world is because MPC offers a mutual relationship between simplicity and performance (Dubay, 2006). Along the way, many developments have been put forward to improve the efficiency of the controller and to address the difficulties faced in applications.

MPC makes process models as a central point and uses them explicitly in the controller (Clarke, 1996; Camacho and Bordons, 1998; Dougherty, 2002; Dougherty and Cooper, 2003a; Qin and Badgwell, 2003). Therefore, in MPC, the model occupies a paramount position (Wang, 2009). It is used to predict the future output (Richalet *et al.*, 1978) due to changes in the process, either change the set point (set point tracking) as well as disturbance change (disturbance rejection).

Getting the best model is an important issue in the MPC. Wahid and Nararya (2015) have successfully improve the models used in the MPC using the system re-identification (SRI). Therefore, this method will be used in this study to control the synthesis of methanol and dimethyl ether (DME).

Experimental Method

The model used was the transfer function of FOPDT (first-order plus dead-time) empirical model. It was derived from the system identification of each controlled variable. Using MPC, carry out system re-identification (SRI) by giving the set-point and disturbance changes on the controller to get a new the process reaction curve (PRC). The SRI was carried out repeatedly for each controller until the value of IAE (integral of absolute errors) generated was worse than previous IAE, which means that the previous model was the best model.

After getting the best model, the parameter tuning was then performed using the Dougherty-Cooper method (Dougherty and Cooper, 2003) and fine tuning. As a comparison of control performance was the PI (proportional-integral) controller and MPC non-tuning.

To simulate the process control, used a process simulator called Uni Sim produced by Honeywel.



Results and Discussion

Determining Controlled Variables

There are six controlled variables (CVs) in the system under study, as shown in Figure 1. The six CVs are the temperature on the heater 1 and 2, the temperature on the cooler 1 and 2, the pressure in the compressor and the composition of DME in the reactor. For each CV selected the appropriate manipulate variables and desired operating conditions (set points) in order to run with the optimum process. All of that can be seen in Table 1.

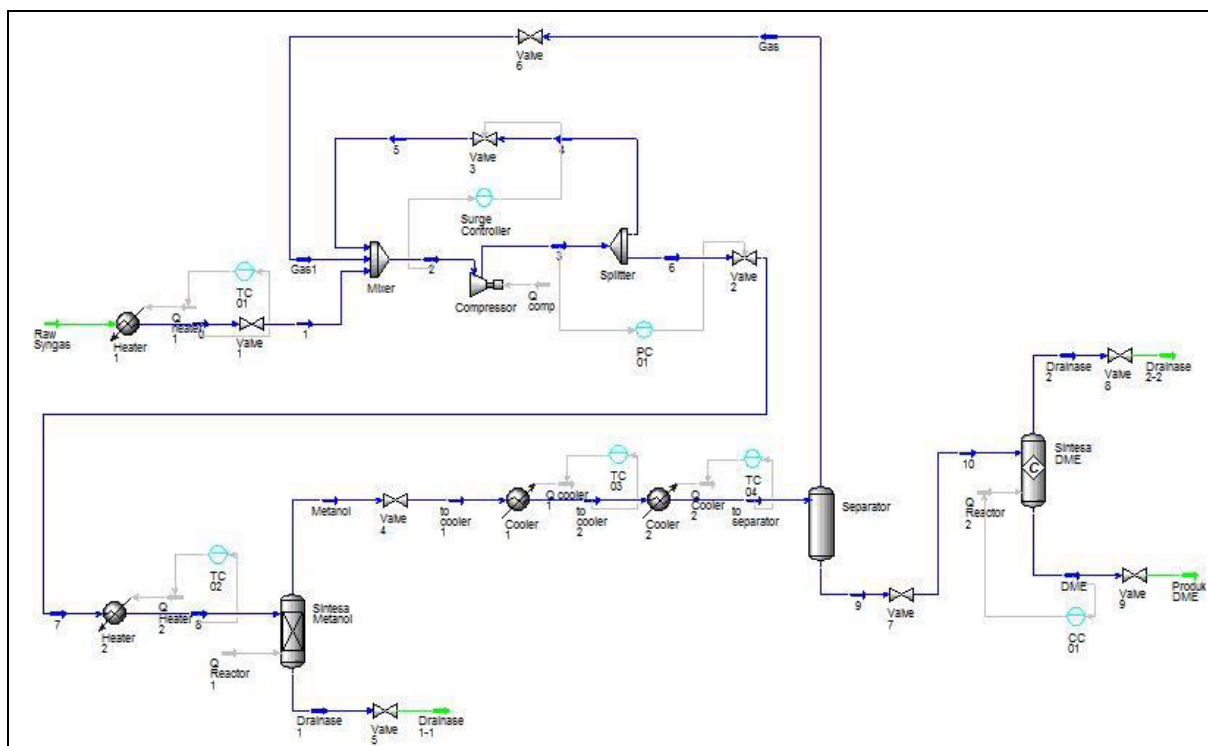


Figure 1. Control systems of methanol and DME synthesis

Table 1. CV, MV and set points in the methanol and DME synthesis

No.	Processes	Controlled Variable	Set Point	Manipulated Variable
1	Heater 1	Temperature	150 °C	Heat flow
2	Heater 2	Temperature	1500 °C	Heat flow
3	Cooler 1	Temperature	1200 °C	Heat flow
4	Cooler 2	Temperature	100 °C	Heat flow
5	Compressor	Pressure	59.5 bar	Output flow rate of compressor
6	DME Reactor	DME mole fraction	0.55	Reactor heat flow

Determining the Best Models

Determining the best model for each controller using SRI produced some PRCs, as shown in Figure 2. All the PRC have been obtained from converting PRC into FOPDT empirical model that is characterized by three parameters, namely the process gain (K_p), time constant (τ) and dead-time (θ). Those parameters are used for two things, namely as a model in the MPC and to set three main parameters MPC (sampling time, T_s , prediction horizon, P_h , and control horizon, M). The results are shown in Table 2. In the calculation of parameters T_s , P_h and M , there are some parameters that doesn't input into the range of values that can be used on UniSim. For example in Cooler 1, the P_h value calculation result was 1123 and the Compressor, the P_h value was 441. Because the upper limit of the P_h value is 400, if the calculation result exceeds 400, will be determined value is 400.

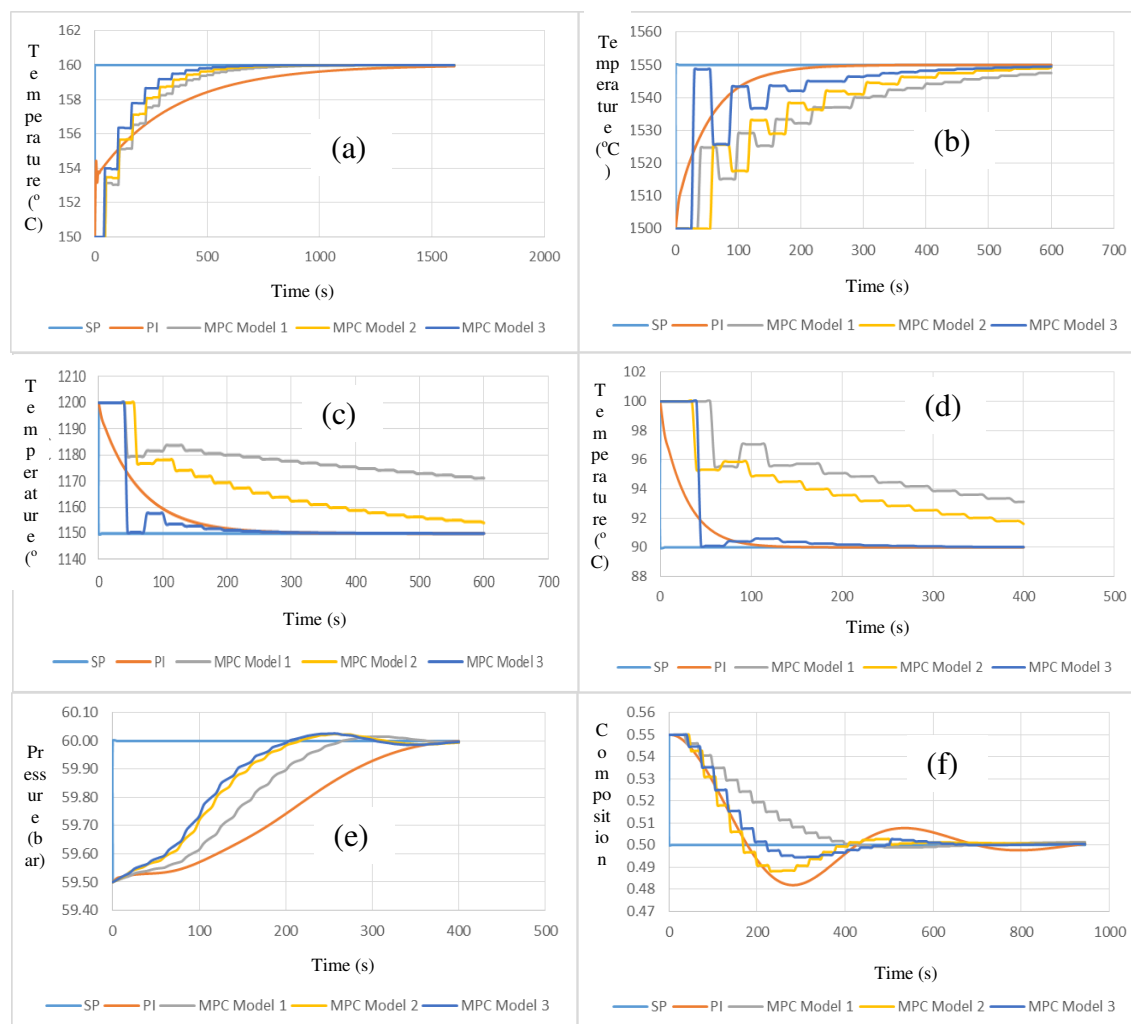


Figure 2. PRC of (a) Heater 1, (b) Heater 2, (c) Cooler 1, (d) Cooler 2, (e) Compressor, (f) DME composition

Table 2. FOPDT models and their MPC's tunings

Models	K_p	τ	θ	$0,1 \tau$	$0,5 \theta$	Trs	Ts (min)	Krs	Prs	P	Mrs	M
T1.1	1,2	0,195	0,145	0,0195	0,0725	0,0725		6,8	45,8		14,6	
T1.2	1	0,15	0,1	0,015	0,05	0,05	0,025	5	35	45,8	11	14,6
T1.3	0,8	0,12	0,05	0,012	0,025	0,025		3	27		7,8	
T2.1	2	0,8	0,007	0,08	0,0035	0,08		1,28	161,28		33,28	
T2.2	1,5	0,5	0,003	0,05	0,0015	0,05	0,05	1,12	101,12	301,28	21,12	61,28
T2.3	0,5	1,5	0,007	0,15	0,0035	0,15		1,28	301,28		61,28	
T3.1	-3	5,5	0,55	0,55	0,275	0,55		23	1123		243	
T3.2	-1	1,5	0,1	0,15	0,05	0,15	0,1	5	305	1123	65	243
T3.3	-0,1	1	0,03	0,1	0,015	0,1		2,2	202,2		42,2	
T4.1	-3	2	0,15	0,2	0,075	0,2		7	407		87	
T4.2	-1,5	1,5	0,08	0,15	0,04	0,15	0,13	4,2	304,2	407	64,2	87
T4.3	-0,075	1,3	0,005	0,13	0,0025	0,13		1,2	261,2		53,2	
P1.1	-0,5	2	1	0,2	0,5	0,5		41	441		121	
P1.2	-0,09	1,7	0,8	0,17	0,4	0,4	0,35	33	373	441	101	121
P1.3	-0,08	1,66	0,7	0,166	0,35	0,35		29	361		95,4	
C1.1	0,5	1,15	0,25	0,115	0,125	0,125		11	241		57	
C1.2	0,15	1,3	0,005	0,13	0,0025	0,13	0,125	1,2	261,2	301,28	53,2	61,28
C1.3	0,25	1,5	0,007	0,15	0,0035	0,15		1,28	301,28		61,28	



Controller Performances

After getting the empirical model and the optimum parameter settings of MPC, conducted testing to determine the performance of the control system design. Test on the system control uses two types of tests, i.e. set-point (SP) tracking and disturbance rejection. Testing the set point tracking was applied to each controller separately to obtain the optimum control parameter settings. While the change in disturbance (feed flow rate), will look at how well a controller in disturbance rejection. This was carried out after the overall controllers were installed at optimum settings.

The magnitude of the set-point change is different for each controller, but the amount was not more than 10%. To change the feed flow rate value can be carried out by changing the feed pressure due to the pressure change also means changing the flow rate. The amount of disturbance change was 0.25 bar (25 kPa). The test results of set-point tracking and disturbance rejection, can be seen in Figure 3 and Figure 4.

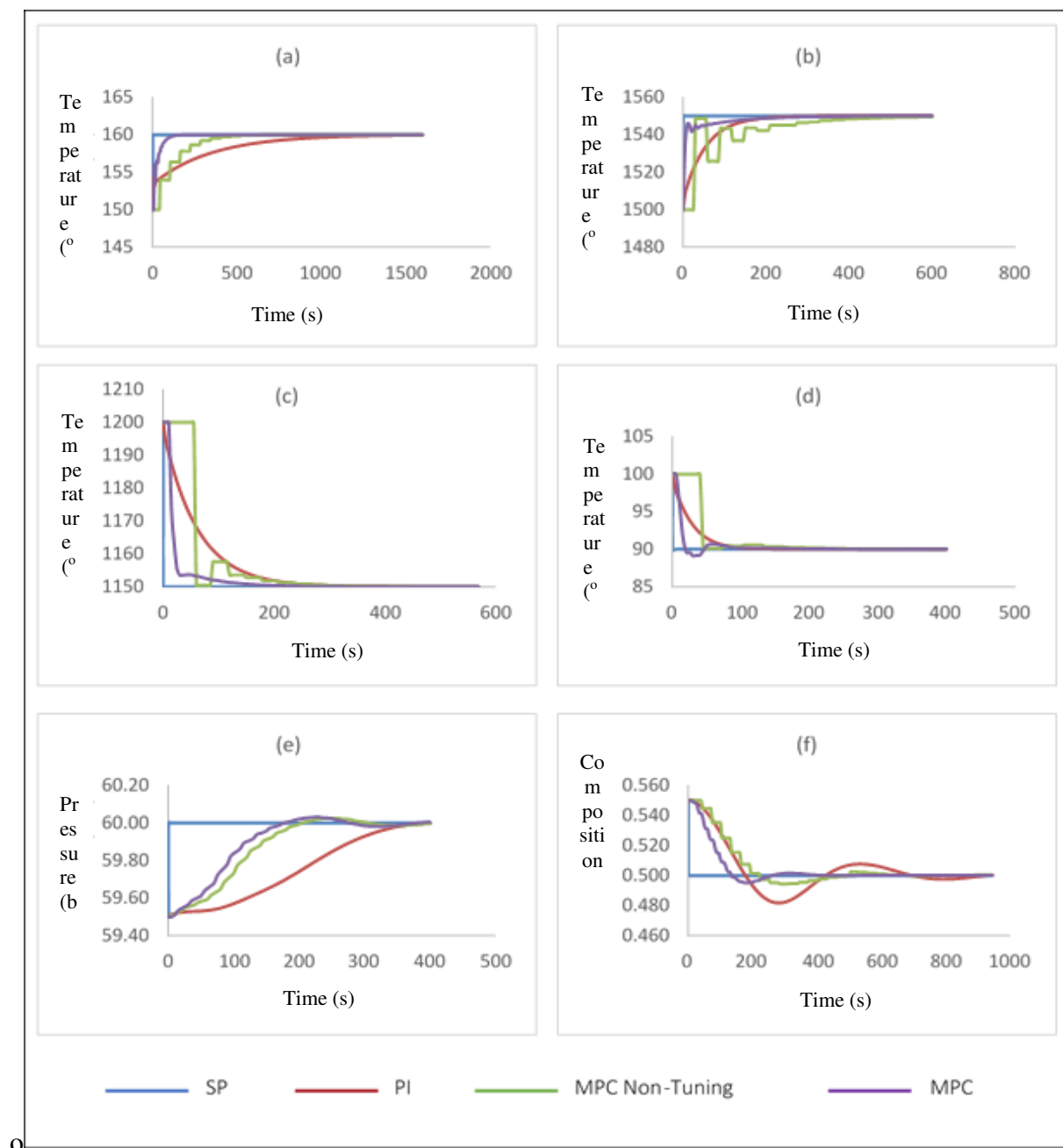


Figure 3. Controller performance of (a) Heater 1, (b) Heater 2, (c) Cooler 1, (d) Cooler 2, (e) Compressor, (f) DME composition, as a result of set-point changes

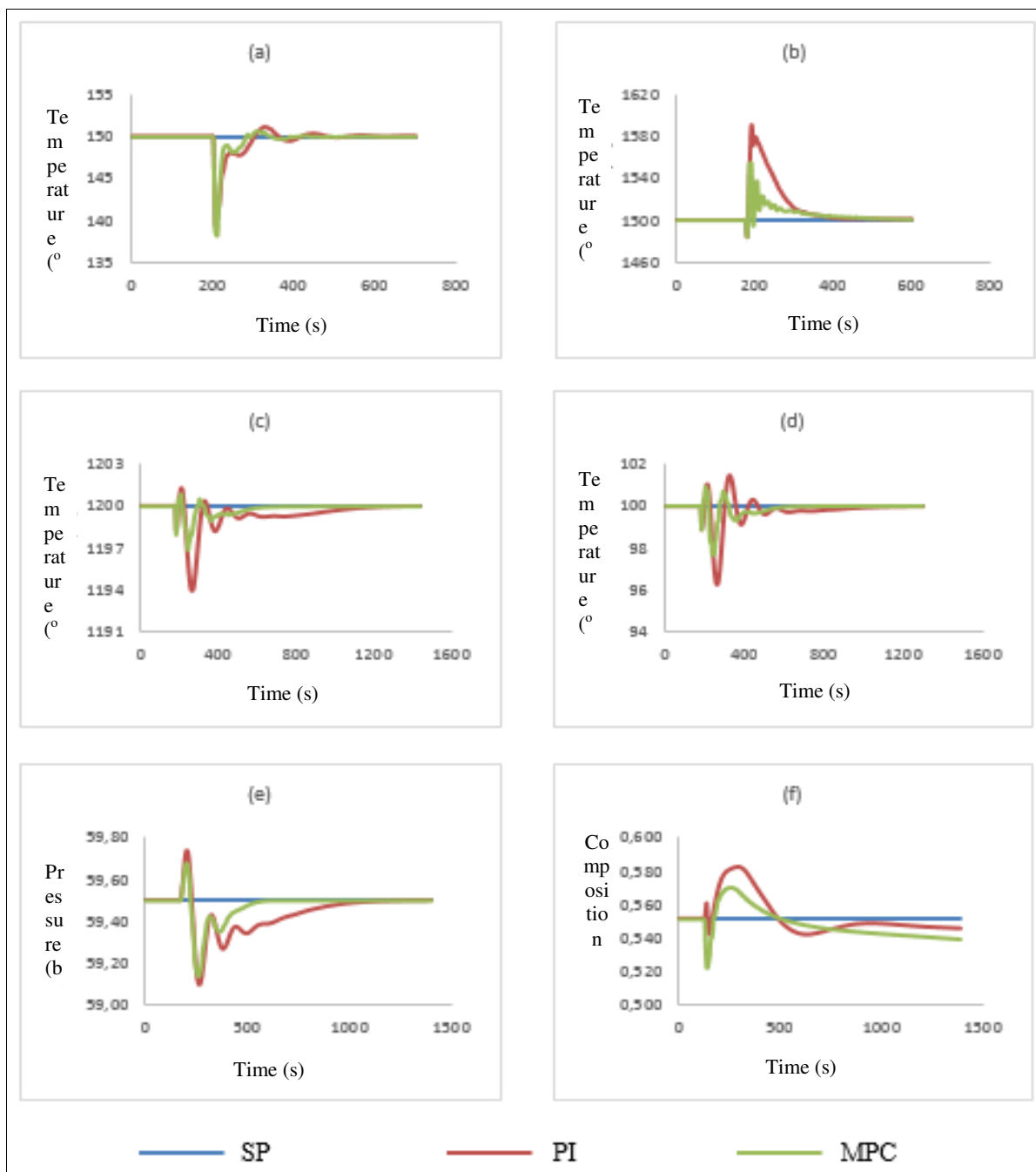


Figure 3. Controller performance of (a) Heater 1, (b) Heater 2, (c) Cooler 1, (d) Cooler 2, (e) Compressor, (f) DME composition, as a result of disturbance change (0.75% of feed flow rate change)

Based on Figure 3 and Figure 4, it can be seen that the MPC gives a better response in maintaining the condition, compared with the PI controller and MPC Non-Tuning. MPC can reach the new set-point (in the set-point change) and maintain the set-point (in the disturbance rejection) with a faster time. Comparison of the control performance of MPC with the PI controller and calculation of their error reduction can be seen in Table 3. The level of performance improvement was significant, i.e., from 4.5% to 67.4% (IAE), or 1.5% to 82% (ISE).

As a note, that the optimization of control, can be carried out using a Dougherty-Cooper method. However, some of the results of Dougherty-Cooper do not provide a good control performance, or even did not react at all to disturbance change given. This can be happen due to their incompatibility of CV ranges used on the controller. The Dougherty-Cooper approach was limited to a relatively small operation range, so as to shift the operating range slightly from a range that is supposed, will provide a very significant impact on the performance of the control system.

Tabel 3.Improvement of control performance

No	Controllers	Parameters					
		IAE			ISE		
		PI	MPC	Error Reduction (%)	PI	MPC	Error Reduction (%)
1	TC Heater 1	80,01	56,31	29,62	359,55	354,12	1,51
2	TC Heater 2	1298,29	627,26	51,69	62101,63	13013,74	79,04
3	TC Cooler 1	174,28	56,74	67,44	382,01	67,83	82,24
4	TC Cooler 2	80,86	41,18	49,07	124,85	40,87	67,26
5	PC Compressor	19,05	8,24	56,75	3,30	1,55	53,03
6	CC DME	2,24	2,14	4,46	0,04	0,02	50,00

Conclusions

System re-identification (SRI) can improve the empirical models used in the MPC. The control performance improvement is significant because it can reach 67% (IAE) or 82% (ISE) in the reduction of errors. The use of the Dougherty-Cooper approach can be carried out with a requirement for Prediction Horizon(P_h) is not greater than 400.

Notation Lists

K_p = process gain
 M = control horizon
 P = pressure [bar]
 P_h = prediction horizon
 T = temperature [°C]
 T_s = sampling time [s]
 τ = time constant
 θ = dead-time

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Lembar Tanya Jawab

Moderator : Endang Kwartiningsih (UNS Surakarta)

Notulen : Andri Perdana (UPN "Veteran" Yogyakarta)

1. Penanya : Deddy Hermawan (UPN "Veteran" Yogyakarta)
Pertanyaan : Tuning Parameter PJ, menggunakan penelitian atau tuning lama Gangguan 0,75% atau 75% sangat kecil sedikit sekali?
Jawaban : Parameter. Habibre 2014, tuning optimum, dilanjutkan MPC penelitian ini. Teori, disturbance $\leq 10\%$. Untuk tahapan selanjutnya dapat dilakukan variasi disturbance sesuai dengan gangguan normal di industry.
2. Penanya : Bambang Harjanto (Politeknik Elektronika Negeri Surabaya)
Pertanyaan : Pengendalian, pengukuran fix, (kondisi fix) base apa?
Jawab : Nilai set point dari pabrik DME – methanol, dalam kondisi steady state dari penelitian sebelumnya.
Penanya : Endang K (UNS Surakarta)
Pertanyaan : Proses yang ada di pabrik atau pilot plant?
: Proses berkelanjutan penelitian dari pabrik yang ada bukan plant DMC-metanol